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Support vector machine method for classifying severity of Alzheimer's based on hippocampus object using magnetic resonance imaging modalities

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ABSTRACT

Alzheimer's disease is a degenerative brain condition that causes progressive decline in several aspects. Starting from memory, cognitive or thinking abilities, speaking abilities, and behavior. Currently, Alzheimer's diagnosis uses some methods, such as blood tests, scanning with computerized tomography scan (CT scan), or magnetic resonance imaging (MRI). As a reference for determining the level of severity, doctors usually use clinical dementia rating (CDR). CDR is a numerical scale used to measure the severity of dementia symptoms. The doctor will manually compare the patient's condition with those stated on the CDR. This condition will take quite a long time, and sometimes human error will occur. As technology and science develop, doctors can assist in manually detecting Alzheimer's using classification algorithms. Many methods can be used to classify, including the CDR support vector machine (SVM) method. Unfortunately, this method is usually only used to classify two classes. This technology allows the classification process to be carried out automatically and quickly. On the other hand, when using CDR to classify Alzheimer's severity, there are several scales, not just two classes. So, in this research, we modified the use of SVM to classify three levels of severity, namely scale 0 for normal, scale 1 for mild conditions, and scale 2 for moderate conditions. The experiments we carried out provided an accuracy of 90.9%.

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1. INTRODUCTION

Alzheimer's is the most common neurodegenerative disease and is the most common form of dementia. The exact cause of Alzheimer's is not fully understood, but the pathological process involves the formation of amyloid-beta plaques in the brain and the accumulation of neurofibrillary tangles. These plaques and tangles disrupt communication between nerve cells and cause nerve cell damage and death. Alzheimer's symptoms involve progressive cognitive decline, such as memory loss, difficulty thinking, and behavioral changes. Patients with Alzheimer's may have trouble performing everyday tasks, recognizing people they know, or organizing their thoughts. Currently, there is no cure for Alzheimer's, but there are symptomatic treatments and management strategies that can help slow the progress of the disease and improve the patient's quality of life. People with Alzheimer's throughout the world are increasing rapidly. Currently, it is estimated

that close to 46.8 or 50 million people are diagnosed with dementia in the world and 20.9 million in Asia Pacific. There are around 10 million new cases every year. In Indonesia, it is estimated that there were around 1.2 million people with dementia in 2016, which will increase to 2 million in 2030 and 4 million people in 2050 [1]. Diagnosis of Alzheimer's is often a complex process and requires a thorough assessment by an experienced healthcare professional. One way to support the diagnosis of Alzheimer's disease is to carry out a brain scan, especially to see the condition of the hippocampus and ventricle areas.

Medical image processing through the magnetic resonance imaging (MRI) modality has experienced significant developments with technological advances and the development of image analysis methods. Some research that uses digital image processing technology in Alzheimer's cases is as follows. Dara *et al*. [2] conducted a comparative study of more than eighty publications on Alzheimer's diagnosis that utilize machine learning and more than fifty papers that discuss approaches with a particular architecture. The conclusion he came to was that all the technology that was already in use needed improvement to become better. Prasath *et al*. [3] studied the need for strategies in medical image processing and analysis for Alzheimer's diagnosis. Zhao *et al*. [4] studied the use of deep learning in improving the quality and efficiency of magnetic resonance imaging or Positron emission tomography in diagnosing Alzheimer's. Vinh and Byeon [5] studied deep learning, especially the you only look once (YOLO) architecture, in neuroimaging and machine learning for Alzheimer's diagnosis. Alghamedy *et al*. [6] used machine learning in medical image-based Alzheimer's classification. In the pre-processing process, they use the contrast-limited adaptive histogram equalization (CLAHE) algorithm to improve image quality; then, classification is carried out using machine learning. Sharma *et al*. [7] researched retinal optics using optical coherence tomography (OCT) images in Alzheimer's patients. This OCT analysis is used to identify the thickness of the retinal layers and changes in the ratio, which can be used as markers for the severity of Alzheimer's. Shastri *et al*. [8] used a 12-layer convolutional neural network (CNN) consisting of 4 convulsion layers, four convolutional, two pooling, two flattened, one dense, and three activation functions to carry out MRI image-based Alzheimer's classification. Xing *et al*. [9] converted 3D images into 2D fused images using the learnable weighted pooling (LWP) method to improve training efficiency and maintain model performance in Alzheimer's diagnosis. Cui *et al*. [10] conducted an in-depth review of the integration of deep learning techniques in medical image recognition across a range of specific approaches, including various modalities for application to Alzheimer's diagnosis. Bamber and Vishvakarma [11] developed a model for diagnosing and tracking the progression of Alzheimer's severity using a CNN based on a shallow convolution layer. Na *et al.* [12] analyzed hearing changes in Alzheimer's patients using transgenic amyloidosis with mice. They concluded that the hearing changes correlated with amyloid deposits in the auditory brainstem and were initially reversible through increased cholinergic signals. These results can potentially be used as an early biomarker for Alzheimer's diagnosis. Zhuo *et al.* [13] used an Ultraweek biophoton imaging system and synaptosomes prepared by a modified Percoll method. This method evaluates functional changes in synapses and nerve networks in people with Alzheimer's and vascular dementia. Francis and Pandian [14] combine the Xception, InceptionV3, and MobileNet layer algorithms that have previously been trained. This algorithm was tested based on T1 weights on Alzheimer's MRI images. Liu and Wang [15] used the Pitt dataset in Alzheimer's detection with a balanced number of genders and ages. The first bidirectional encoder representation of the trained transformer model is used to obtain the word vector. Then, two channels are built in the feature extraction layer: a convolutional neural network and long- and short-term memory models to extract local and global features, which will be used in classification. In our previous research [16]–[18] we developed a system for Alzheimer's classification based on low-resolution MRI images. However, in this research, our focus was only on coronal cross-sections, even though MRI images have three types of cross-sections: coronal, sagittal, and axial. Hence, the results we got in previous research could have been more optimal. The main goal of conducting this research is to obtain integrated information from three axial, sagittal and coronal cross-sections to support cataract diagnosis based on the support vector machine (SVM) method.

In this paper, we make improvements by extracting features on the three cross-sections to make the resulting classification more comprehensive. In this paper, we will discuss how to apply the SVM classification algorithm to the classification of Alzheimer's brain image objects based on an extensive hippocampus dataset on coronal, axial, and sagittal images, as well as calculating the accuracy level of classification of Alzheimer's brain image objects using the SVM method.

2. PROPOSED METHOD

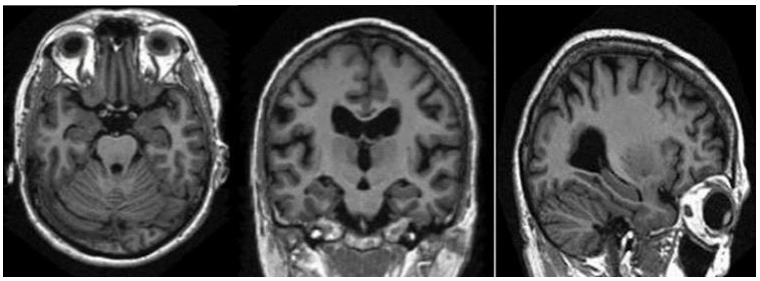
In this research, we modified the support vector machine method to carry out multilevel classification. The system we developed begins by entering the image data to be tested into the system; then, the test image will be segmented to obtain the required objects. The segmentation results will determine the area of the object in the image being tested. After the test image data has been obtained, the data will be compared with the existing dataset to calculate the probability. SVM classification can only be used to

classify two classes. Therefore, we use multilevel SVM classification to be able to classify more than two classes. In our system, initial level classification classifies MRI image parameter data of the hippocampus brain suffering from Azheimer's disease and normal (not suffering from Azheimer's disease). If SVM identifies the test data as suffering from Alzheimer's, the data will proceed to advanced classification. However, if the data is identified as not suffering from Alzheimer's, the system will immediately show a clinical dementia rating (CDR) result of 0, meaning it does not suffer from Alzheimer's. Advanced classification: Data that has undergone initial classification and the results of identifying the data as suffering from Alzheimer's will go through an advanced classification process. This advanced classification will determine the severity level of people with Alzheimer's based on CDR 1 (mild) and CDR 2 (moderate) classes.

3. METHOD

3.1. Input image

Alzheimer's disease is an irreversible and progressive brain disorder associated with changes in nerve cells, causing brain cell death. Alzheimer's disease occurs gradually, is not part of the normal aging process, and is the most common cause of dementia [19]. Meanwhile, the CDR is a scale for evaluating dementia severity, especially for Alzheimer's. This research used three severity scales: a scale of 0 to indicate normal conditions, a scale of 1 for mild conditions, and a scale of 2 for moderate conditions [20]. This research uses image data from open access series imaging studies (OASIS). The initial data consisted of cross-sectional data collection from 416 subjects aged 18 to 96 years. One hundred subjects aged over 60 years have been clinically diagnosed with Alzheimer's disease in the mild to moderate category [21]. Figures 1(a) to (c) show an example of three cross-sectional MRI images (axial, coronal, and sagittal) used in this study.



(a) (b) (c)

Figure 1. An example of three cross-sectional MRI input images, (a) axial, (b) coronal and (c) sagittal

3.2. Image processing

Image processing is processing images to improve the quality, explicitly using computer assistance. In image processing, there is a processing process called segmentation. Image segmentation aims to separate objects that will be needed to obtain their characteristics from objects that will be left alone. Generally, the output of image segmentation results is a binary image with the desired object being white (1) while the unwanted object is black (0). Like the image quality improvement process, the image segmentation process is also experimental, subjective, and depends on the goals to achieve [22]. The segmentation method applied in this research is active contour. This research used magnetic resonance imaging (MRI) data from Azheimer's brain image with the joint photographic experts' group (jpg) extension. MRI image data is divided into three types of planes: axial, coronal, and sagittal. Based on each area of the MRI image of the brain, part of the hippocampus will be visible, which is the object of segmentation to be used as a parameter to determine the severity of people living with Alzheimer's. The results of cutting or cropping the hippocampus in the brain MRI image then enter the feature extraction stage. The feature extraction stage aims to extract specific values or variables that are unique characteristics of an object. These values or variables are used to classify objects into particular categories or classes with similar or the same characteristics as several available classes.

3.3. Classification

Classification is the grouping of an object into one of the predetermined categories. The target function learning process (classification model) will map each set of attributes (input) to one of the

previously defined classes. Input is a training data set with class attributes in this data. Based on the class attributes, a classification model will be determined to obtain a classification model. Classification models are usually used to separate objects with the same characteristics into the same class, while objects with different factors will be grouped into various classes. In this research, we use the SVM classification method. In simple terms, the concept of SVM is to find the best hyperplane that functions to separate two classes in the input. The basic principle of SVM is a linear classifier, which was further developed to work on non-linear problems. The best way to separate the hyperplane between two classes can be determined by measuring the margin of the hyperplane. The margin is the distance between the hyperplane and the closest pattern from each class [23].

4. RESULTS AND DISCUSSION

In this research, we use polygon cutting. Polygon cutting was chosen because it can adjust the shape of the hippocampus quite well so that a neat cutting shape is obtained and is centered only on the hippocampus. Figures 2, 3, and 4 show examples of cropping stages used to obtain hippocampus objects in MRI brain images by cutting polygons in the sagittal, axial, and coronal planes. The following process features extraction after the cropping stage is carried out properly until the desired test object is obtained. The feature extraction used in this research is image segmentation using the active contour method. Active contour uses the principle of minimizing energy, which detects certain features in the image and is a flexible curve that can adapt dynamically toward the desired edge boundary or object [24].

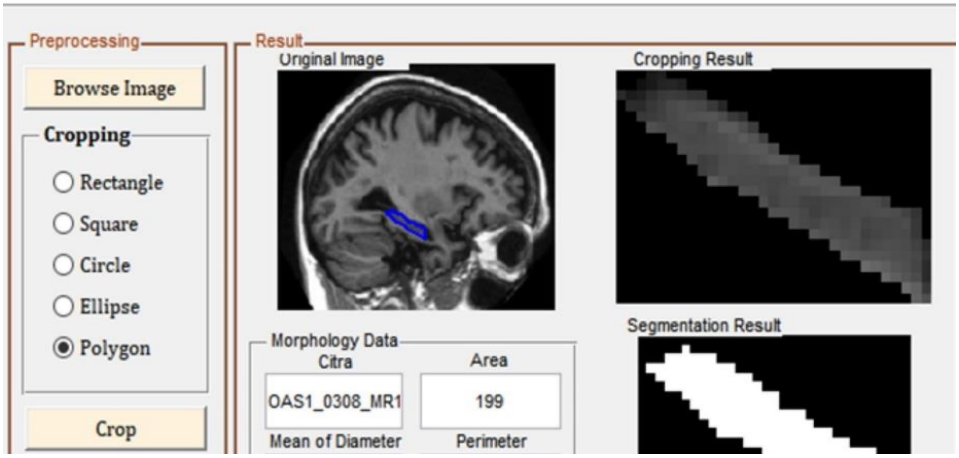


Figure 2. Cropping stages in the sagittal plane with polygons

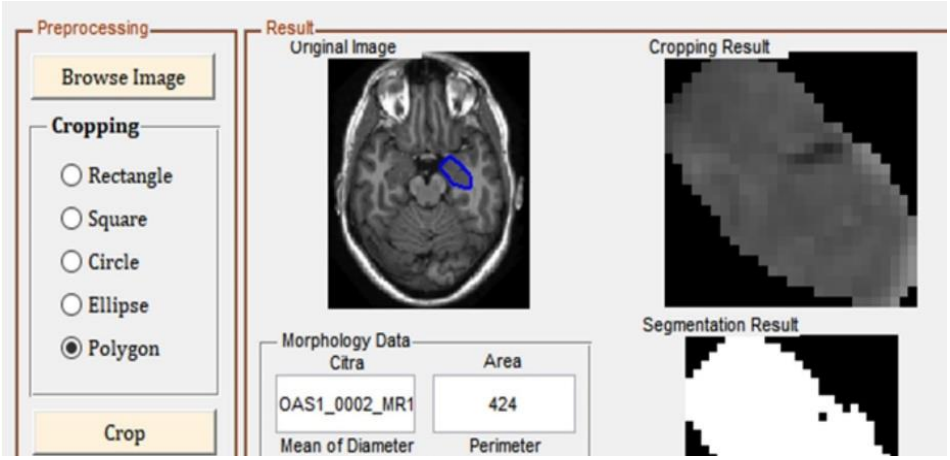


Figure 3. Cropping stages in the axial plane with polygons

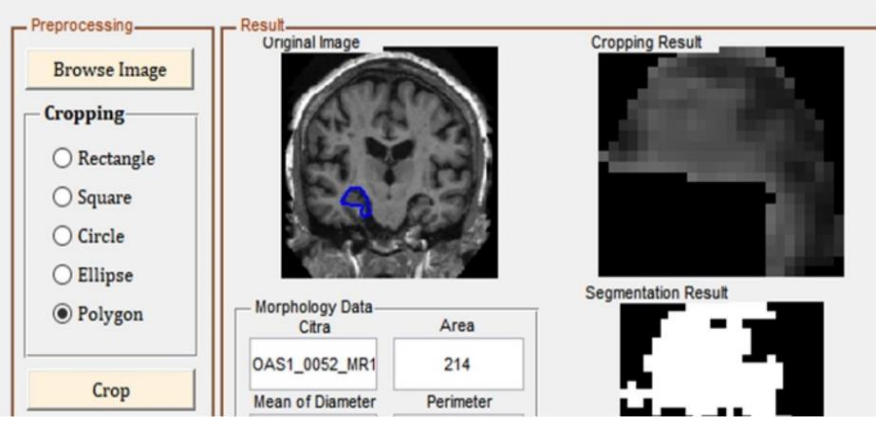


Figure 4. Cropping stages in coronal plane with polygons

From the segmentation results, the characteristic parameters of the object resulting from hippocampus MRI brain image cropping are obtained in the form of area, diameter, and perimeter values. These characteristic parameters are used as training and test data at the classification stage. Figures 5 to 7 show examples of the feature extraction stages obtained from axial, sagittal, and coronal MRI brain image sections. In Figure 5, the area parameter value is 424, the average diameter is 23.32347, and the perimeter is 82.669. It is classified in the CDR category 0. In Figure 6, the area parameter value is 214, the average diameter is 16.5068, and the perimeter is 96.3259, classified in the CDR category 1. In Figure 7, the area parameter value is 199, the average diameter is 15.9177, and the perimeter is 79.2548, classified in CDR category 2. The segmentation results in characteristic parameters are then stored to form a data set, which will later be used as training and test data in the SVM classification method. The distinctive data resulting from MRI image extraction of the brain in the hippocampus was then classified based on CDR class using the SVM classification method.

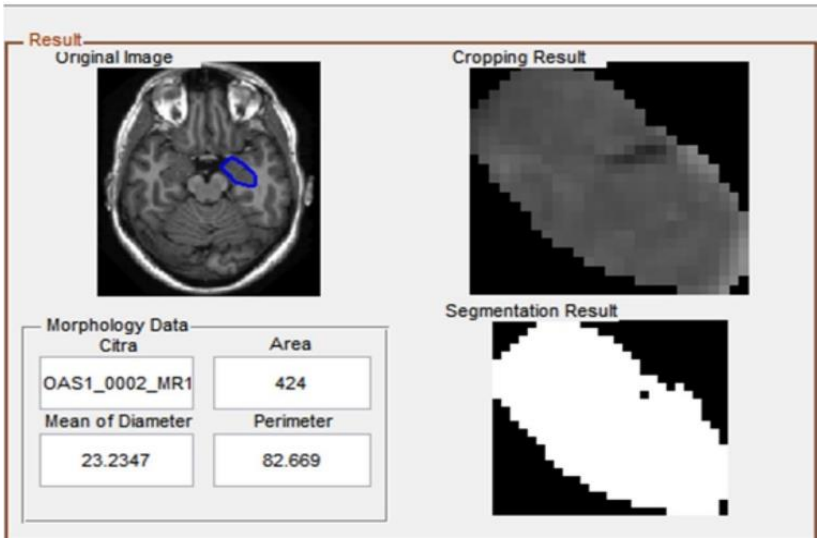


Figure 5. Feature extraction in axial cross-section

SVM requires training by storing the support vector results to be used again during prediction or testing. SVM is not affected by high data dimensions, so it has no reduction process. The memory in an SVM is influenced by the amount of data, not the size of the data dimensions. In the initial stage of SVM classification training and prediction experiments, the training data is 44 data objects consisting of 3 cutting planes (coronal, sagittal, and axial), so the total image data used is 132 from 44 objects. The mixture of Alzheimer's brain MRI image data consists of 28 class 0 data and 16 class 1 data. Class 1 data is MRI image

data of brains that are detected to be suffering from Alzheimer's at both CDR 1 and CDR 2 levels. At the initial classification prediction stage, the system will identify data that suffers from Alzheimer's and average data (not suffering from Alzheimer's). Next, we separate class 1 data for training data for advanced SVM classification predictions. This advanced SVM classification data consists of MRI images of brains predicted to suffer from Alzheimer's level CDR 1 and CDR 2 from 3 MRI planes: axial, coronal, and sagittal. We carried out SVM classification testing using a system that we have developed. The aim is to determine how accurate the SVM method is for classifying Alzheimer's objects based on brain MRI image data that we obtained from the OASIS database. The test uses 3 MRI image-cutting planes: axial, coronal, and sagittal. The characteristic data of the three cutting planes is classified into specific classes based on the CDR value using the SVM algorithm that has been created. The initial stage uses active contour segmentation to take characteristic data from 3 MRI fields with the same object—feature extraction.

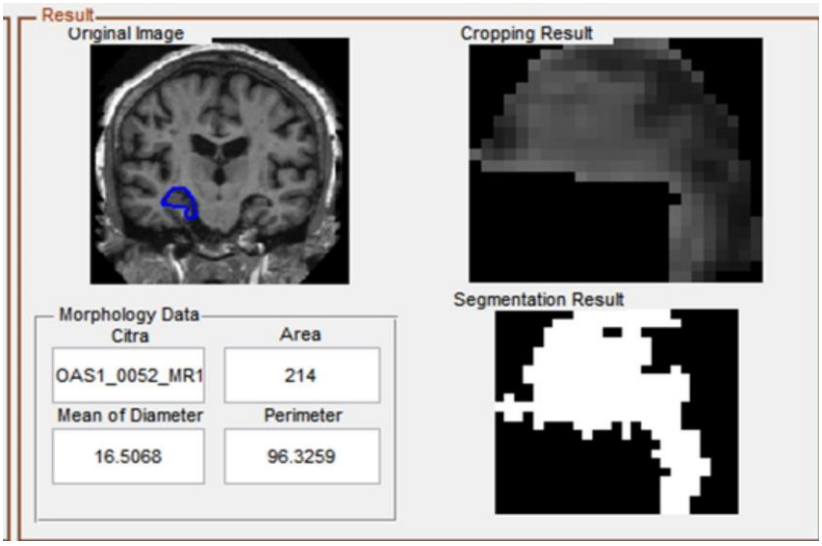


Figure 6. Feature extraction in coronal cross-section

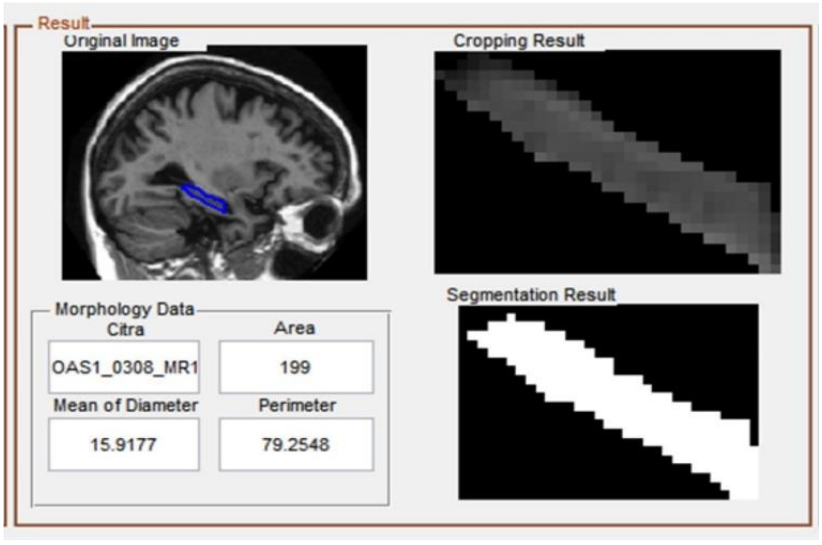


Figure 7. Feature extraction in sagittal cross-section

Feature extraction is used to obtain characteristic values from test data in SVM classification. The large-scale image is cut or taken from the hippocampus as a classification object. The hippocampus is part of the limbic system. The limbic system is the part of the brain involved in behavioral and emotional responses. The primary function of the hippocampus is learning and long-term memory storage. Therefore, if someone

experiences Alzheimer's, the hippocampus will shrink, becoming smaller than ordinary people's [25]. The characteristic variables taken from the hippocampus slice image of the brain are the pixel size of the hippocampus area, the perimeter, and the diameter of the hippocampus. People living with Alzheimer's will have smaller pixel values of the hippocampus area compared to ordinary people. These characteristic variables are processed using active contour segmentation. The following is the feature extraction data obtained from 66 MRI images, consisting of 22 MRI images in the axial plane, 22 in the coronal plane, and 22 in the sagittal plane. The results of all test data are a combination based on the results of the classification prediction data in the three areas of the brain MRI image that we display in Table 1.

Table 1. Classification result

No	Image	Classification Result	Target	Information
1	OAS1_0002_MR1_mpr_n4.bmp	CDR0	0	matching
2	OAS1_0013_MR1_mpr_n4.jpg	CDR0	0	matching
3	OAS1_0020_MR1_mpr_n3.jpg	CDR0	0	matching
4	OAS1_0157_MR1_mpr_n4.jpg	CDR0	0	matching
5	OAS1_0044_MR1_mpr_n4.jpg	CDR0	0	matching
6	OAS1_0130_MR1_mpr_n4.jpg	CDR0	0	matching
7	OAS1_0135_MR1_mpr_n4.jpg	CDR0	0	matching
8	OAS1_0165_MR1_mpr_n3.jpg	CDR0	0	matching
9	OAS1_0169_MR1_mpr_n4.jpg	CDR1	0	**not match**
10	OAS1_0170_MR1_mpr_n4.jpg	CDR0	0	matching
11	OAS1_0308_MR1_mpr_n4.jpg	CDR2	2	matching
12	OAS1_0308_MR1_mpr_n4.jpg	CDR2	2	matching
13	OAS1_0351_MR1_mpr_n4.jpg	CDR2	2	matching
14	OAS1_0052_MR1_mpr_n4.jpg	CDR1	1	matching
15	OAS1_0073_MR1_mpr_n4.jpg	CDR1	1	matching
16	OAS1_0351_MR1_mpr_n4.jpg	CDR1	1	matching
17	OAS1_0073_MR1_mpr_n4.jpg	CDR1	1	matching
18	OAS1_0184_MR1_mpr_n4.jpg	CDR0	1	**not match**
19	OAS1_0185_MR1_mpr_n4.jpg	CDR1	1	matching
20	OAS1_0035_MR1_mpr_n4.jpg	CDR1	1	matching
21	OAS1_0278_MR1_mpr_n4.jpg	CDR1	1	matching
22	OAS1_0291_MR1_mpr_n4.jpg	CDR1	1	matching

Based on the data in Table 1, MRI images were tested in 3 axial planes, coronal sagittal, with 22 data, consisting of 10 CDR 0 data, 9 CDR 1 data, and 3 CDR 2 data. The predicted data is then compared with the actual target value based on data from OASIS; it can be seen that the values in the prediction results of 20 data are by the desired target CDR, while 2 data are not by the target. Data on object number 9 (*OAS1_0169_MR1_mpr_n4.jpg*) and object number 18 (*OAS1_0184_MR1_mpr_n4.jpg*) are not classified according to the target data. In the *OAS1_0169_MR1_mpr_n4.jpg* data classified at CDR 1, it should be CDR0, while the *OAS1_0184_MR1_mpr_n4.jpg* data classified at CDR 0 should be CDR 1. This condition can happen because it is not accurate when cutting the area of the edge of the hippocampus, so the test data classification results do not get an appropriate value. Based on the accuracy and error calculations, it can be seen that the test results have an accuracy percentage of 90.9% and an error percentage of 9.09%. The results of testing the classification system using SVM show excellent accuracy. Errors occur because the image quality does not meet standards, so the hippocampus area cannot be segmented properly. This condition causes the classification process to experience mistakes, as listed in Table 1.

5. CONCLUSION

This study's accuracy level reached 90.9% in testing with brain MRI image planes (axial, coronal, sagittal) with characteristic parameters resulting from hippocampus image segmentation using the active contour and polygon cutting methods. The more training data in the SVM will increase the chances of better predictions because the memory in the SVM depends on the amount of data, not on the size of the dimensions of the training data. The cutting stage of the hippocampus in the MRI image of the brain becomes very important; the neater and more accurate the hippocampus is cut, the more precise the segmentation characteristic data will be. The SVM classification method can be developed by adding training and test data to obtain exact accuracy values. The system can be created and compared with feature extraction using methods other than active contour and cutting techniques. For further research, it is necessary to consider using image quality that meets the requirements for image-based classification.

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